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Multivariate and spatial analysis of reduced urban air pollution during COVID-19 pandemic in Delhi

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Abstract

Towards the end of 2019, a novel contagious virus (COVID-19) came out of Wuhan, China and turned into a disastrous pandemic. Many countries were completely or partially locked down. The ongoing pandemic has greatly affected our society and economy but, on the other side, it had effects upon the natural environment, as it rejuvenated itself. The present study repots the air quality and spatial distribution of air quality parameters (PM_{10}, $PM_{2.5}$, NO_2, SO_2, O_3 and CO) in Delhi, taking into account data from 36 monitoring stations, for the months of January - April 2019 and 2020, respectively before and during the COVID-19 pandemic. The statistical tools like box plot, Pearson's correlation, and PCA were used to interpret air pollution data before and during the lockdown period. The results revealed the characteristics of pollutants with respect to location, relationship between pollutants, and monitoring their level in compliance with the limits set by the legislation. The results of multivariate analysis were further spatially analyzed by mapping the distribution of pollutants by using the Inverse Distance Weighted interpolation. The result revealed the gradual reduction in the pollutant concentrations (PM_{10}, $PM_{2.5}$, CO, SO_2) and an increment in ozone concentration was observed, which was due to a drastic reduction in NO_2, especially during March and April 2020, immediately after the declared lockdown in the region. The overall study indicated that the interventions for urban air pollution mitigation are crucial in the regeneration of nature.

Keywords: *COVID-19, multivariate data analysis, spatial interpolation, air quality, IDW, Delhi*

Rezumat. Analiza spațială multivariată a poluării reduse a aerului în Delhi în timpul pandemiei de COVID-19

Spre sfârșitul anului 2019, un nou virus contagios (COVID-19) cu originea în Wuhan, China a determinat o pandemie dezastruoasă. Multe țări au fost închise complet sau parțial. Această pandemie a afectat foarte mult societatea și economia noastră, dar a avut și efecte asupra mediului natural, care s-a regenerat. Prezentul studiu raportează calitatea aerului și distribuția spațială a parametrilor calității aerului (PM_{10}, $PM_{2.5}$, NO_2, SO_2, O_3 și CO) în Delhi, folosind date de la 36 de stații de monitorizare, pentru lunile ianuarie - aprilie 2019 și 2020, respectiv înainte și în timpul pandemiei COVID -19. Instrumente statistice precum Diagrama Boxplot, Corelația Pearson și Analiza Componentelor Principale/PCA, au fost utilizate pentru a interpreta datele privind poluarea aerului înainte și în timpul perioadei de lockdown. Rezultatele au evidențiat caracteristicile poluanților în ceea ce privește locația, relația dintre poluanți și monitorizarea nivelului acestora în conformitate cu limitele stabilite de legislație. Rezultatele analizei multivariate au fost ulterior analizate spațial, prin cartografierea distribuției poluanților, utilizând interpolarea IDW. Rezultatul a relevat reducerea treptată a concentrațiilor de poluanți (PM_{10}, $PM_{2.5}$, CO, SO_2) și s-a observat o creștere a concentrației de ozon datorită unei reduceri drastice a NO_2, în special în perioada martie-aprilie 2020, imediat după blocarea declarată în regiune. În general, studiul a indicat că intervențiile pentru atenuarea poluării aerului urban sunt cruciale în regenerarea naturii.

Cuvinte-cheie: *COVID-19, analiza multivariată a datelor, interpolare spațială, calitatea aerului, IDW, Delhi*

Introduction

In December 2019, a novel contagious disease named COVID-19, belonging to the coronavirus family, was diagnosed in Wuhan city of China (Chen, 2020). WHO validated in January 2020 that it is transmitted among humans through respiratory globules. The spread of this disease was found to be extremely rapid in the surrounding area of Wuhan. In late January 2020, it was termed as an epidemic by the authorities and, subsequently, WHO declared a worldwide health emergency (Dutheil et al., 2020). In the following month of February 2020, it flared up in many other countries like Italy, Iran, etc. In due course of time, it became pandemic. It was the end of March 2020, when more than half of the world's population had been under one or another form of shutdowns (Tosepu et al., 2020). By the middle of April 2020, because of COVID-19, more than 2.1 million cases were confirmed all around the world, with a total of 135,000 deaths (WHO, 2020).

Due to global lockdown, the industrial, manufacturing and the transportation sectors were severely affected. However, transportation was most affected, as both road and air traffic began to restrict the local as well as international movement of people. The restriction resulted in the drop of air traffic by 96%. While human health was impacted massively and the world economy simply crashed by COVID-19, the restrictions also resulted in the betterment of air quality, by reduced emissions into the atmosphere (Tobías, 2020).

One of the most detrimental and inevitable consequences of urbanization and industrialization is the release of air pollutants. The WHO estimates that about 90% of urban residents experience air pollution that exceeds WHO guidelines and that air pollution is responsible for more than four million premature deaths annually. Vehicles and industrial emissions include a lot of air pollutants.

Theoretical background

The major pollutants responsible for the degradation of air quality in urban areas are oxides of nitrogen (NOx), oxides of carbon, oxides of sulphur (SOx), ozone and particulate matter (SPM and RSPM) (Batterman et al., 2007; Bosco et al., 2005; Emami et al., 2018; Marć et al., 2016; Somvanshi et al., 2019; Wu et al., 2011). Particulate matter is a carcinogen and thus raises the chance of heart attacks (Cesaroni et al., 2014; Raaschou-Nielsen et al., 2015). Because of the reactive nature of O_3, it can damage lung tissue and prolonged exposure has been linked to increased heart attack risks (Fann et al., 2012; Khaniabadi et al., 2017a). NO_2 is mainly released by the burning of fossil fuels and it is highly reactive in nature. Vehicles are the major source of NO_2 (He L. et al., 2020; He M. Z. et al., 2020). Several works proved that long term and short term exposures to NO_2 could cause death to human beings (Faustini et al., 2014). Other health hazards caused by this pollutant include respiratory disorders, increased sensitivity to asthma and cellular inflammation. NO_2 and SO_2 are the major contributors to the emergence of asthma and lung cancer (Greenberg et al., 2016; Khaniabadi et al., 2017b). On average, the total human deaths per year due to poor air quality is 4.6 million all around the world. The effects of air pollution are seen in the developed, as well as developing nations. In 2012, Europe, one of the most developed regions, witnessed the death of 193,000 people. Hence, air pollution is a major concern and a global issue (Cohen et al., 2017). Reducing inputs of these pollutants into urban areas requires a combination of technological advancement and behavior change that can be stimulated by governmental regulations and incentives.

Alterations of human, transport and industrial activity are usually the results of long-term economic and behavioral change and they are difficult to legislate under normal conditions. However, this pandemic has brought about certain crisis measures, endeavoring to diminish transmission rates that limit action, development and business in purviews around the world (Bera et al., 2020). While these emergency measures are critically important to limit the spread and impact of the coronavirus, they also provide a glimpse into how governmental calls for behavioral change can alter air pollution levels in cities. Thus, it is essential to study and understand the pattern of changes before and after the lockdown period and, on the basis of outcomes, policy-level changes can be recommended (Elass et al., 2020).

One of the very useful statistical tools to study and analyze large environmental datasets is the multivariate analysis. Another important and useful tool is the correlation analysis that can be used to discern the relationship between various air pollutants or other variables that have an impact on air quality. It is an efficient tool to review the most significant aspects or sources of chemical components, as it has already been used in various air pollution research studies (Binaku & Schmeling, 2017; Tiwari & Singh, 2014; Zhu et al., 2017). Similar to many of the multivariate methods of analysis, the principal component analysis (PCA) is also a method of data reduction that considers the correlation between the studied parameters, as the significant number of parameters in the dataset is small (Sharma et al., 2020). Due to its usefulness in data interpretation and classification, it is widely used in the environmental analysis (Wilks, 2011; Mostert et al., 2010). PCA is used to discover existing relationships between meteorology and concentrations of various air pollutants along with other techniques like canonical correlation analysis.

Spatial interpolation methods can also be used to study air pollution analysis (Akita et al., 2014; Li & Heap, 2014). For environmental studies of science and management, spatially continuous data of different ecological variables is needed. Nevertheless, in the case of mountainous regions and deep oceans, point sampling is carried out in order to obtain information about environmental variables. Hence, to convert the point sampling to spatially continuous data, different generating methods become important tools. Spatial interpolation is one such method, but it is usually data-specific or sometimes even variable specific. The predictive performance of the methods is affected by a lot of factors and studies have proved that these effects are inconsistent. Therefore, the selection of a suitable method for a particular dataset is tedious. Several interpolation methods are depending upon the data involved, such as local and global interpolation. The Ordinary Kriging (OK) and Inverse Distance Weighted (IDW) are the most frequently used local interpolation methods, which estimate the value with standard error for the unsampled point based on value and distance of the neighboring sample points.

Additionally, continuous upgradation of instruments and advancement in technique has led to the detection of a significant number of pollutants, even with very little concentration (Mitra et al., 2020). When collecting air quality information from monitoring stations, although there is a small number of sampling points, useful information can be obtained by using multivariate methods that are adequate to characterize a given scenario or situation in full (Hajmohammadi & Heydecker, 2021). Applying statistical methods such as box plots, multivariate correlation analysis and PCA, along with geostatistical analysis like IDW interpolation can represent a very useful tool in the air quality data interpretation (Kumari et al., 2021).

Hence, the purpose of this research is to investigate the effect of the unconventional intervention of the Indian Government regarding the lockdown on the levels of nitrogen oxides, ozone, sulfur dioxide, carbon monoxide and particulate matter (PM_{10} & $PM_{2.5}$), to map the spatial-temporal distribution of these pollutants and to correlate between them during lockdown period and pre-lockdown period.

Study Area

The case study area selected for the current research was Delhi, India's capital city, with coordinates ranging from the latitude of 28°24′17′′ to 28°53′00′ North and the longitude of 76°45′30′′ to 77°21′30′′ East. It is located along the Yamuna river's western bank and occupies an area of approximately 1,490 km^2. It is enclosed in the North by the Himalayas and towards South-West by the Aravali ranges (Figure 1). This city experiences semi-arid climate, having May and June as the hottest months, with temperatures reaching 48°C, while at the end of December-January, the lowest temperatures drop to around 5°C. The monsoon season continues from July to September, with July being the month characterized by maximum rainfall (about 300 mm).

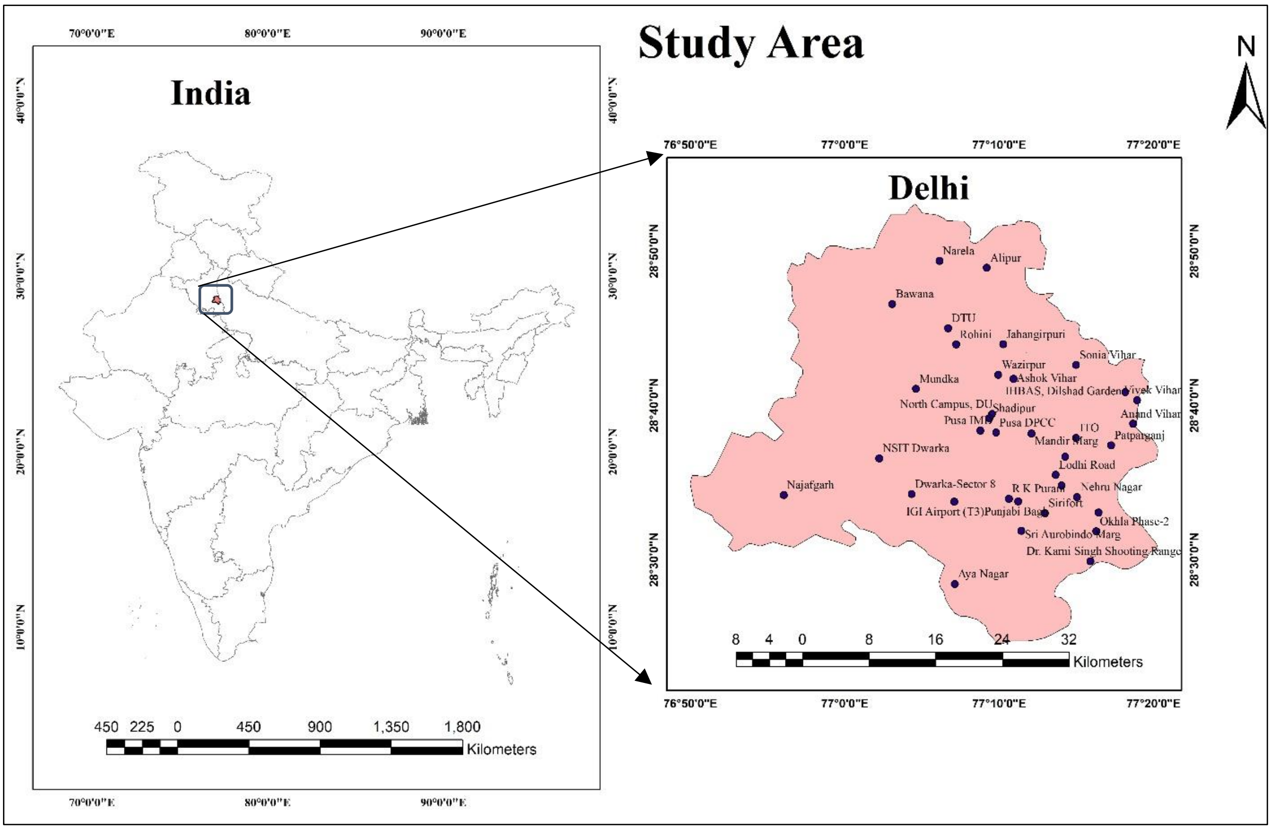

Fig. 1: Study area and ground sampling points

Delhi has been witnessing rapid population growth, i.e. from 1.7 million in 1951 to over 16 million in 2011 (Census 2011), which makes it one of the high spread suburbs in the world. The land use of Delhi is prominently marked by residential, industrial and commercial areas coupled with increased socio-economic activities. The rapid development is also accompanied by urban air pollution, Delhi being identified as one of the most polluted cities of India. Because of the wide spread of COVID-19, a nationwide lockdown was imposed from 24th March to 14th April and it was later extended for many months. To follow social distancing, as a measure of caution almost all industrial activities and mass transportation was prohibited. As a result, the pollution level in Delhi was drastically reduced.

Material and methods

Data Used

In Delhi NCR, more than 70 continuous air quality monitoring sites were developed by the Central Pollution Control Board (CPCB), in association with other local environmental protection agencies, in order to protect the air quality of the ambient environment. Such sites monitor and map the level of air pollutants. The data concerning the air pollutant concentration levels from these sites include hourly concentrations and 24-hour average concentrations (daily-mean). For the present study, hourly measurements of all the selected parameters ($PM_{2.5}$,

PM_{10}, NO_2, SO_2, Ozone, and CO) were collected from 36 sites of Delhi NCR (Official website of Central Control Room for Air Quality Management managed by CPCB) (Figure 1). The analysis compared the two time periods: period 1 is from 1st January till 30th April 2019 and period 2 is from 1st January till 30th April 2020.

Multivariate Air Quality Data Analysis

The statistical tools employed in this study are box plots, Pearson's correlation, and PCA. The most significant step in temporal analysis is plotting the observational data against time. A Box Plot, sometimes also known as the whisker plot, is useful in the detection and comparison of outliers. Python-based box plots were developed for all the air quality parameters and for both periods, in order to graphically present the data according to their quartiles. The correlation coefficient is a statistical method to calculate the degree of association among variables when measured in pairs for comparison. Pearson's correlation coefficient is mostly used in linear regression. In this study, it is used to measure the degree of association between seven air contaminants.

To lower the dimensionality of a dataset (usually normally distributed), a multivariate technique, namely Principal Component Analysis (PCA) is used. The dataset includes several interrelated variables and converts them into non-correlated variables, which is a new set of variables that in turn, maximize variance. The vast majority of the variation in the dataset can be portrayed by considering a few principal components at whatever point there is a significant correlation between variables. Also, the trends and similarities in the data can be visualized while retaining the information as it is in the original dataset. The Principal components consist of a matrix of correlation or covariance. Every Principal component derives a full proportion of the overall variance. A Principal component shall be considered statistically significant if the own value is greater than or equal to 1 (Kaiser criterion).

Spatial Analysis

To study topological, geometric and geographic properties, spatial and statistical analysis was carried out. There was a similarity in values obtained from nearby points and variability for locations distant from each other. The spatial analysis comprises different techniques, many of which are in their early developmental stage. Different analytic approaches are incorporated in these techniques. One such technique is the spatial interpolation, also called Geo-statistics. Geo-statistics can be described as an important tool that is essential to study the spatial patterns and to calculate the continuous variable values that are dispersed temporally at the locations that are not part of sampling sites. One of the spatial interpolation techniques is that called Inverse Distance Weighted (IDW). This approach works on the assumption that objects closer to one another are more alike in comparison to objects that are farther apart. IDW uses the calculated values surrounding the prediction position to estimate a value for every unmeasured location. The calculated values nearest to the prediction position impact the predicted value more than those farther away. IDW assumes that each measured point exerts a decreasing local impact with distance. It gives higher weights to the points nearest to the position of prediction and influences decrease according to distance. Thus, it is called Inverse Distance Weighted. Geostatistical tools were applied to determine spatial patterns and distribution of air pollutants.

Results and Discussion

Description of the data

Descriptive statistics of the air pollution parameters studied in Delhi have been carried out (Tables 1 and 2). The analysis also includes measures of variability, central tendency and form. The pollutants analyzed in this research were: suspended particulate matter (PM_{10} & $PM_{2.5}$), nitrogen dioxide (NO_2), ozone (O_3), sulphur dioxide (SO_2), and carbon monoxide (CO).

Table 1: Statistical summary of the air pollutants concentrations during January – April 2019

	PM_{10}	$PM_{2.5}$	NO_2	SO_2	O_3	CO
Count	**36**	**36**	**36**	**36**	**36**	**36**
Average	240.79	81.46	58.43	22.20	39.89	1.36
Standard deviation	51.10	17.77	23.99	7.25	19.62	0.56
Coeff. of variation (%)	21.22	21.82	41.07	32.67	49.17	41.34
Minimum	146.30	52.76	3.96	7.59	9,21	0.40
Maximum	336.78	124.66	97.55	40.05	78.18	3.40
Range	190.48	71.89	93.59	32.46	68.97	3.00
Stnd. skewness	0.23	0.43	0.04	0.01	-0.06	1.29
Stnd. kurtosis	-0.73	-0.47	-0.60	-0.60	-1.05	3.85

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Table 2: Statistical summary of the air pollutants concentrations during January – April 2020

	PM_{10}	$PM_{2.5}$	NO_2	SO_2	O_3	CO
Count	36	36	36	36	36	36
Average	101.77	42.75	20.33	13.80	49.38	0.77
Standard deviation	22.72	11.00	7.07	6.29	27.23	0.42
Coeff. of variation (%)	22.33	25.74	34.79	45.56	55.15	54.92
Minimum	68.78	11.94	6.16	1.22	2.21	0.32
Maximum	155.44	64.32	36.40	25.89	93.20	1.95
Range	86.66	52.38	30.24	24.67	91.00	1.63
Stnd. skewness	0.65	-0.53	0.55	-0.11	-0.16	1.28
Stnd. kurtosis	-0.21	1.45	-0.38	-0.70	-1.04	0.74

The study area has witnessed a significant decline of the pollutants after the declaration of three weeks of lockdown starting from 24th of March 2020. During the study period, almost all the pollutants (except ozone - O_3) have shown significant declining trends. In Delhi, the major source of particulate matter (PM_{10} and $PM_{2.5}$) is represented by traffic and construction activities. The average concentrations of these PM_{10} and $PM_{2.5}$ have reduced by approximately fifty percent respectively. Large standard deviations and coefficients of variation were found for the PM_{10} and NO_2 during the pre-lockdown period and for O_3 during the lockdown period, which indicates heterogeneity in the concentrations among the monitoring stations. In both intervals, CO was more skewed (asymmetry of the probability distribution) due to large differences between CO measured at various monitoring stations. Plotting the observations against time is an essential step in time series analysis. The plot describes the data and assists to formulate a reasonable model (Núñez-Alonso et al., 2019).

In the present study we used the Python-based box plot for better interpretation of the results. Using the box plot, it is possible to study the dispersion of all the pollutants and it also helps to understand their monthly trend (Figure 2). The box plot analysis for $PM_{2.5}$ shows that during the months of January and February, the values were more scattered and higher and they appreciably declined during the lockdown duration in the city, namely during March – April 2020. The temporal patterns of PM_{10} values in Delhi showed a significant decline in the months of March and April, 2020 as compared to 2019 levels. However, the highest values were noted in January 2019 as compared to other months. The concentration was much more dispersed in the same month. The least dispersed concentration was observed in the month of April 2020, due to the strict implementation of lockdown during this month in the city.

As presented in the figure, the level of NO_2 in Delhi provides a comparison of NO_2 emissions between 2019 (January - April) and 2020 (January - April). It is evident from the plots that NO_2 concentration has decreased notably during the lockdown period, as there was sustainable reduction in the movement of vehicles and other transportation modes. The reduction in transportation activities and the subsequent decrease in oil demand have a major impact on the concentration of NO_2 in the environment, as the primary source of NO_2 emissions is combustion of fuel in transport (Mahato et al., 2020).

Exceptionally, there was noticeable increase in the case of O_3, although it followed the same trend of decline in concentration. Similarly, SO_2 and CO also showed an exponential decline during the lockdown phase of the city.

Correlation Analysis

Correlations analysis permitted exploring ecological relations amongst the envisaged pollutants, which showed the significant correlation between their sources.

For each pollutant, Pearson's correlation coefficients were significant in all cases with p values$\leq$0.05 (Tables 3 and 4). NO_2 significantly correlated positively with PM_{10}, with coefficient values equal to 0.6261 and 0.5506 in period 1 (January – April 2019) and period 2 (January – April 2020) respectively. NO_2 also showed a significant correlation with $PM_{2.5}$, with the coefficient value equal to 0.5239 for the second period. The photochemical smog in the presence of oxide of nitrogen can be attributed to the presence of the particulate matter in Delhi, with a significant correlation between NO_2 and particulate matter.

As it can be seen, O_3 is negatively correlated with PM_{10} and NO_2, with a Pearson correlation of -0.4015 and -0.5667, respectively in the first period of the study, which consequently decreased in the second period due to the decline in the concentration of the pollutants. PM_{10} significantly correlated positively with $PM_{2.5}$, with coefficient values equal to 0.7590 and 0.7747, respectively, in both periods, which suggested a good association and a common source.

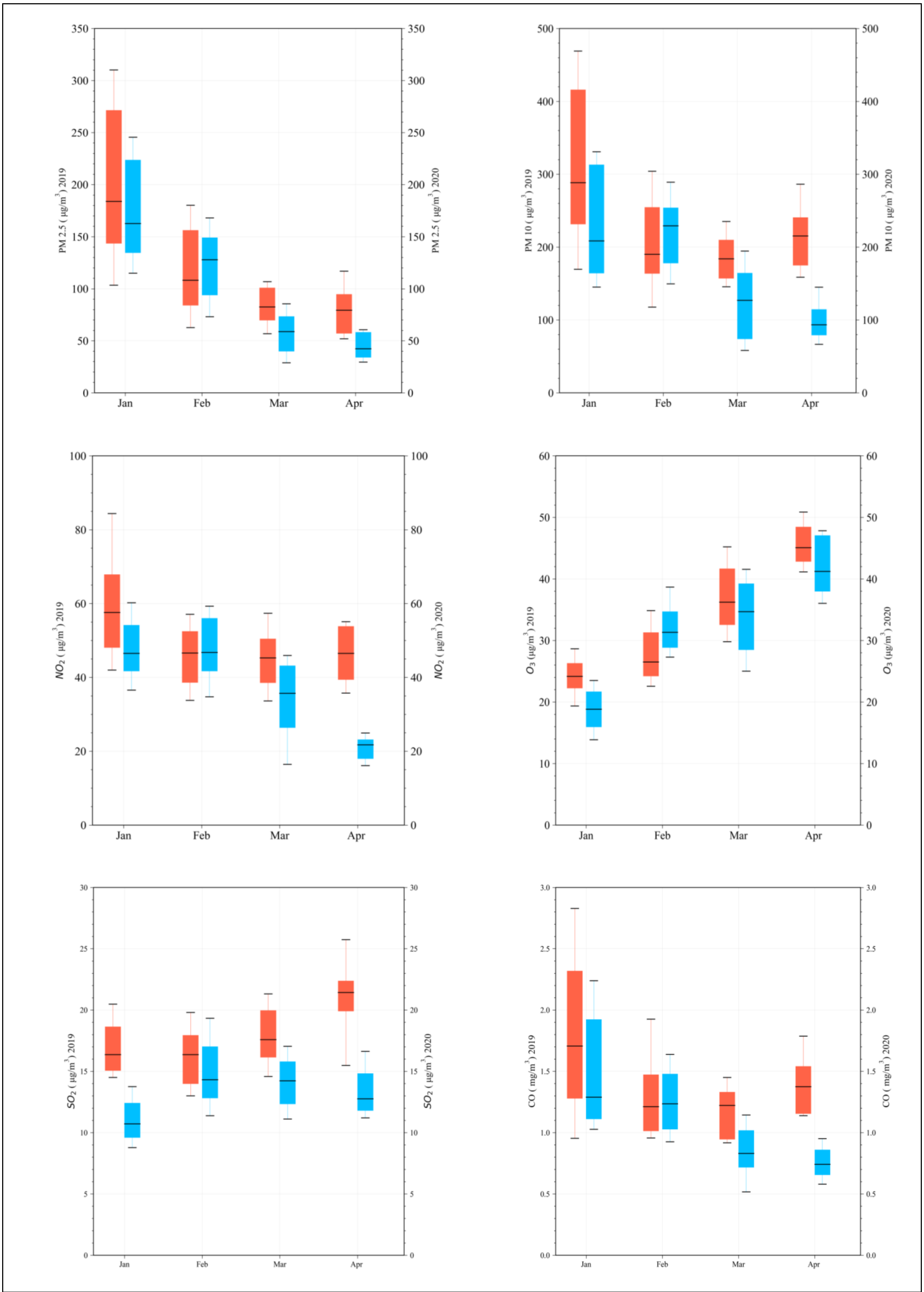

Fig. 2: Temporal comparative analysis of air pollutants

Table 3: Correlation matrix among the six air pollutants for the first time interval (January – April 2019)

	PM_{10}	$PM_{2.5}$	NO_2	SO_2	O_3	CO
PM_{10}	-	0.7590	0.6262	-0.0611	-0.4016	0.1268
$PM_{2.5}$	0.7590	-	0.3504	-0.0226	-0.3214	0.0554
NO_2	0.6262	0.3504	-	0.1352	-0.5667	0.0539
SO_2	-0.0611	-0.0226	0.1352	-	0.1653	0.2701
O_3	-0.4016	-0.3214	-0.5667	0.1653	-	-0.1058
CO	0.1268	0.0554	0.0539	0.2701	-0.1058	-

Table 4: Correlation matrix among the six air pollutants for the second time interval (January – April 2020)

	PM_{10}	$PM_{2.5}$	NO_2	SO_2	O_3	CO
PM_{10}	-	0.7747	0.5507	0.2118	-0.3461	-0.1517
$PM_{2.5}$	0.7747	-	0.5240	0.0936	-0.2065	-0.0665
NO_2	0.5507	0.5240	-	0.2244	-0.3009	0.1347
SO_2	0.2118	0.0936	0.2244	-	-0.3540	0.0817
O_3	-0.3461	-0.2065	-0.3009	-0.3540	-	-0.2029
CO	-0.1517	-0.0665	0.1347	0.0817	-0.2029	-

Principal Component Analysis

Generally, geospatial datasets are difficult to handle and interpret. Hence, to increase the interpretability of the dataset, the reduction of the data dimensionality with less information loss can be done by using PCA. PCA creates a new set of uncorrelated variables that, in turn, maximize variance.

According to Kaiser criteria, the principal components higher than 1 should be retained and, according to this, only three components of 2019 accounted for 81.77 percent of the variation in the dataset. The first component explained about 39.31% of the total variance and it had moderate positive loadings of PM_{10} (0.585) and $PM_{2.5}$ (0.577), which means that parameters under this group were responsive components of air pollution. The second component was responsible for 28.13% of the total variance and it had a moderate positive loading of carbon monoxide (0.518) and a negative loading of ozone (0.661). Vehicular pollution and biomass burning are the major sources of carbon monoxide pollution in the region. The third component explained 14.33% of total variance (Tables 5 and 6).

Table 5: Eigenvalues and accumulated variance of the principal components, 2019

Component number	Eigen value	Percent of variation	Cumulative percentage
1	2.54709	39.3131	39.3131
2	1.35116	28.1333	67.4464
3	1.1747	14.3309	81.7772
4	0.6189	9.2381	91.0153
5	0.21867	6.6244	97.6397
6	0.08148	2.3603	100.0000

Table 6: Eigenvalues and accumulated variance of the principal components, 2020

Component number	Eigen value	Percent of variation	Cumulative percentage
1	2.19304	54.6509	54.6509
2	1.82523	23.9683	78.6192
3	0.91782	10.0398	88.659
4	0.47604	6.9217	95.5807
5	0.32402	3.4108	98.9915
6	0.25687	1.0085	100.0000

In 2020, out of all six components, only two were characterized by Eigen values above 1 and they accounted for 78.61 percent of the variation in the dataset. The first component explained about 54.65 percent of the total variance and it had moderate positive loadings of NO_2 (0.460) and negative loading of SO_2 (0.427) and O_3 (0.531). The second component was responsible for 23.96 percent of the total variance and it had a positive loading of PM_{10} (0.529), $PM_{2.5}$ (0.639) and carbon monoxide (0.467) (Table 7).

Table 7: Factor Loading Component wise for both time intervals

Variable	2019 Factor Loading Component wise			2020 Factor Loading Component wise	
	1	2	3	1	2
PM_{10}	**0.58577**	-0.08478	0.29968	-0.35287	**0.52964**
$PM_{2.5}$	**0.57730**	-0.13411	-0.07424	-0.28847	**0.63967**
NO_2	0.27888	0.27812	**-0.88693**	**0.46018**	0.20953
SO_2	0.37038	-0.43640	0.04022	**-0.42766**	0.00054
O_3	-0.06601	**-0.66191**	-0.21491	**-0.53146**	-0.21964
CO	0.32293	**0.51856**	0.26501	0.33935	**0.46707**

**Statistically significant loadings are marked by bold*

Spatial concentration pattern of major pollutants during lockdown and pre-lockdown phase

The IDW spatial interpolation method was employed to find out the spatial extent of the pollutants and their ranges for both time intervals. These maps showed that $PM_{2.5}$ were generally dispersed all through the city, even surpassing the yearly normal breaking point for the assurance of human wellbeing, i.e. 60µg/m^3 and ranged in category of very poor to poor during the first period (2019); subsequently, during April 2020, due to lockdown implementation by the government, $PM_{2.5}$ was within the permissible limits, i.e. in the category of moderate to satisfactory (Figure 3). The northwestern part of the study area, mainly including the western peripheral highway and the major districts of Bawana, Mangolpuri, and Model Town was the most affected by the PM_{10} pollutant that fell under the very poor to severe category (Nigam et al., 2021). However, a significant decrease in concentration was evident in April 2020, ranging from satisfactory to good category (Figure 4).

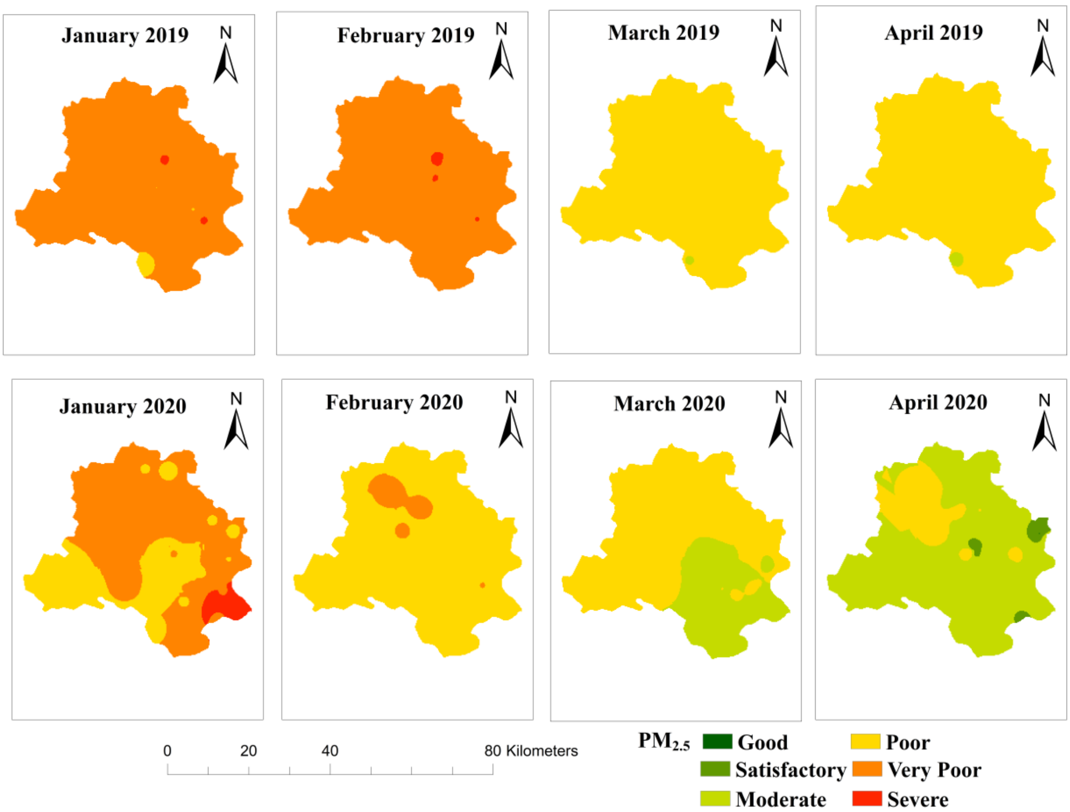

Fig. 3: Spatial comparative analysis of $PM_{2.5}$

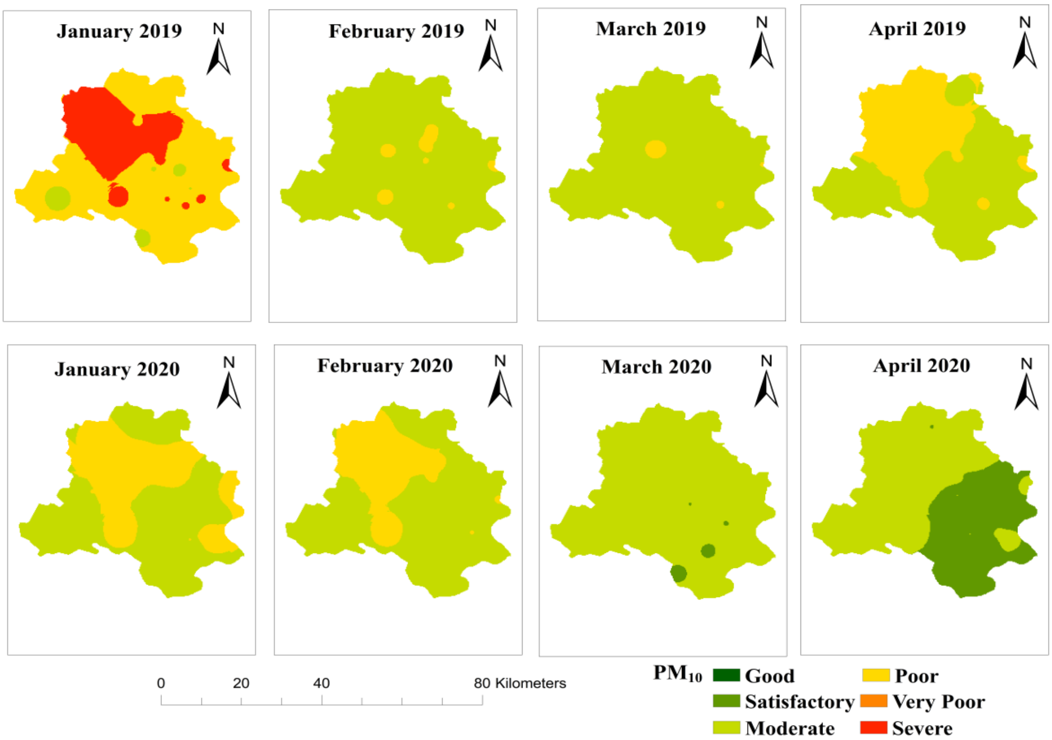

Fig. 4: Spatial comparative analysis of PM_{10}

The major source of NO_2 in the urban area is represented by vehicle transportation and manufacturing or industrial units. During the lockdown, all these activities were hampered and there was a significant decline in the NO_2 level in April 2020, ranging under satisfactory to good category (Figure 5). In the O_3 and SO_2 interpolation map, it can be observed that during both periods, i.e. before and during lockdown, the concentration of both these pollutants was within the average limit prescribed by the government and ranging between satisfactory to good category (Figures 6 and 7). A similar trend is observed in CO, although it was within the permissible limit throughout the study interval (Figure 8).

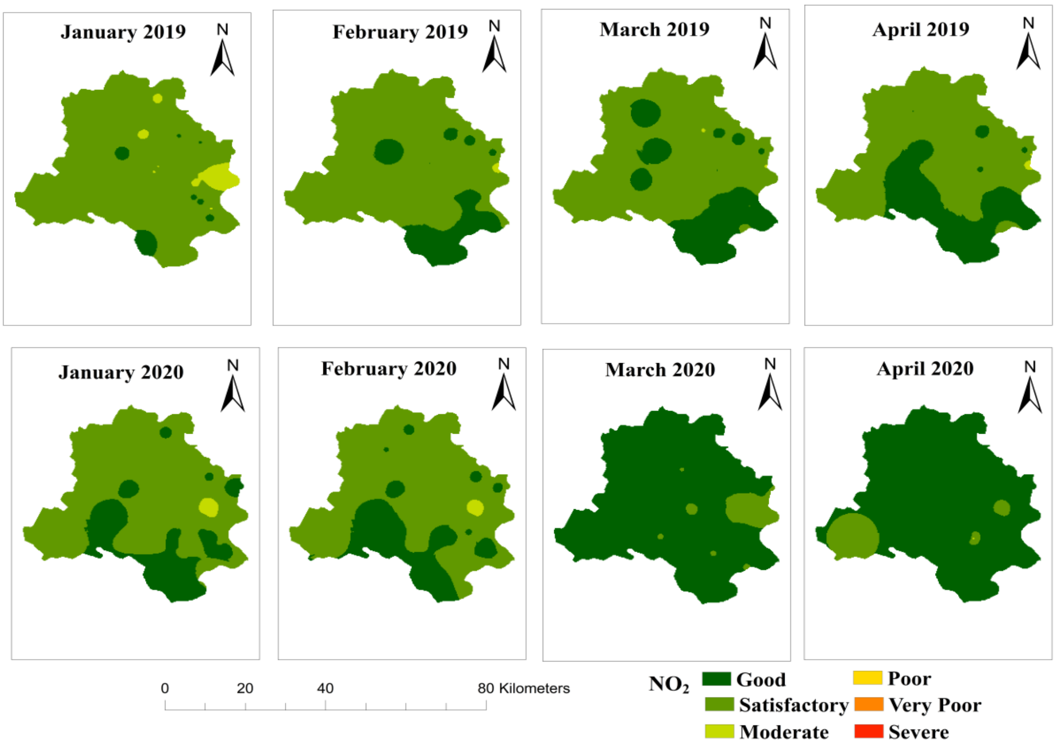

Fig. 5: Spatial comparative analysis of NO_2

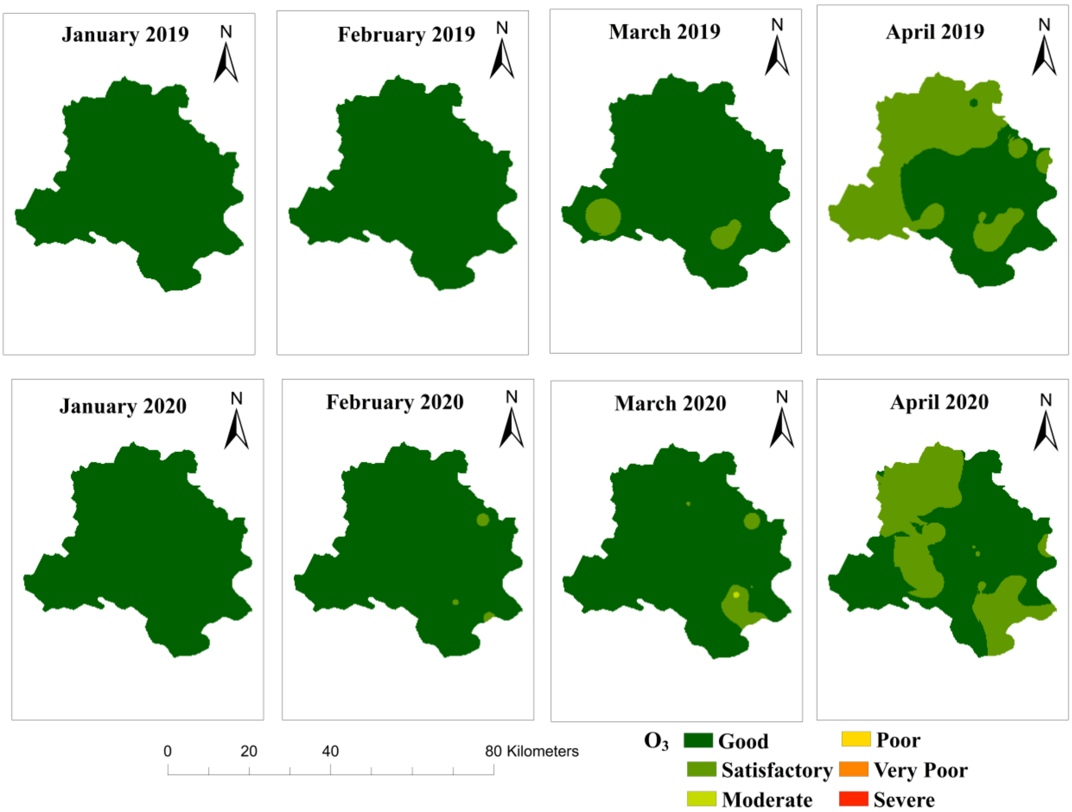

Fig. 6: Spatial comparative analysis of O_3

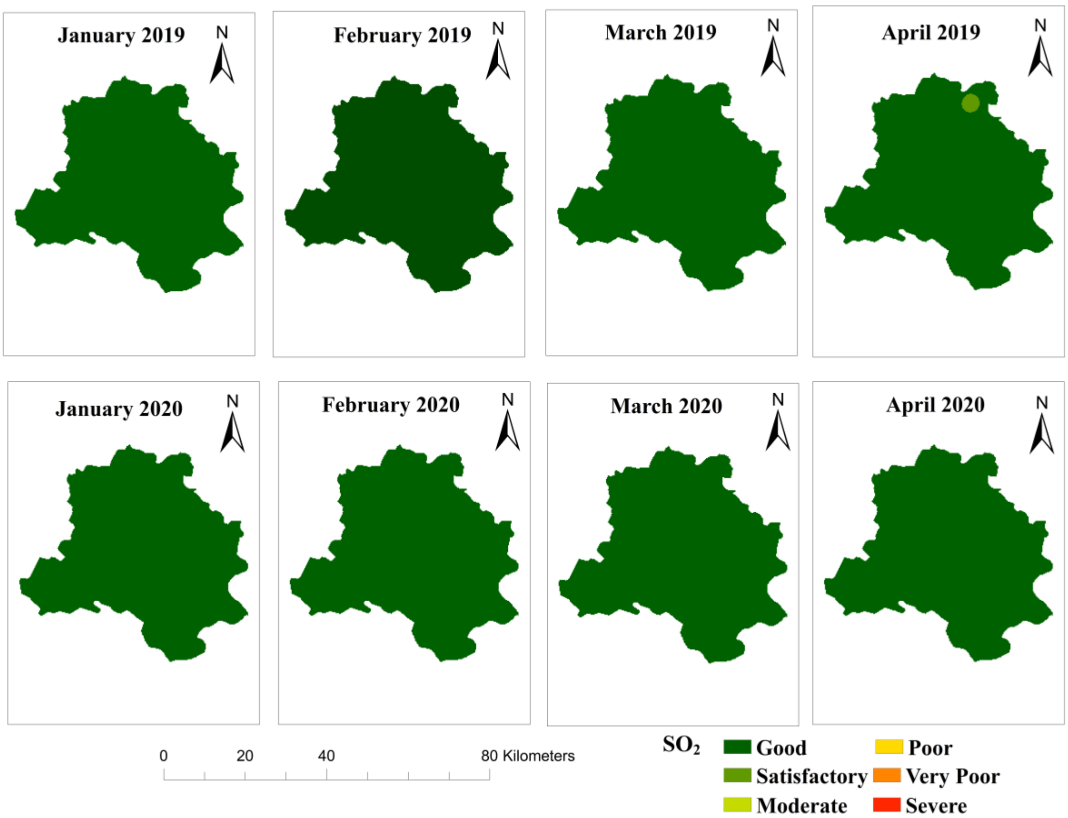

Fig. 7: Spatial comparative analysis of SO_2

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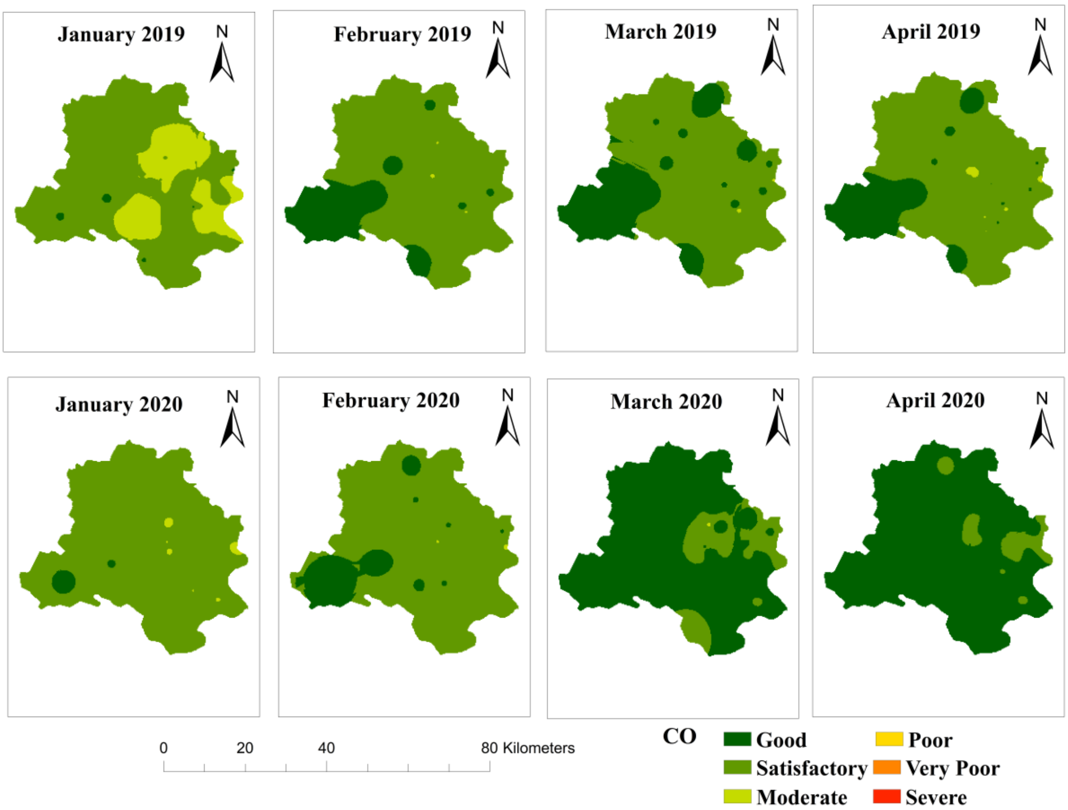

Fig. 8: Spatial comparative analysis of CO

The trend of all six air quality parameters was studied by using the geostatistical analysis for two significant periods (before and during lockdown). A decreasing trend in the levels of all parameters has been observed between the two periods, for the months of March and April. This is the aftereffect of the air quality improvement during the advancement of COVID-19 pandemic, generally marked by the decrease of street traffic emissions. Another reason concerns the decrease of industrial activities in the area (Garg et al., 2021).

As the urban ecosystem mainly focuses on socio-economic growth and overlooks the various environmental issues, such as pollution, it is exposed to a health threat. The environmental restoration process has drawn significant attention for the analysis of air pollution in the course of the pandemic.

Conclusion

COVID-19 has now become a pandemic all around the world and it poses a severe threat to human wellbeing, while also hindering monetary exercises. Nevertheless, it has surprisingly ensued positive development in environmental aspect. The pollution of environment is declining and nature is recovering itself. In the present study, the six major air pollutants of Delhi were compared between pre-lockdown and during lockdown period. Among the selected pollutants, the significant reduction was in PM_{10} and $PM_{2.5}$, followed by NO_2, SO_2 and CO, due to suspension of all industrial and transportation activities. On the other hand, due to the decrease in the concentration of NOx and particulate matter, there was a slight increase in O_3 concentration. Perhaps this effect is not permanent, but it is positive on the environment. Also, governments and people ought to gain from this lockdown the most proficient method to decrease pollution on long term basis.

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